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The Application of New Adaptive PSO in AGC and AFC Combination Control System

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Abstract

This paper presents a method to solve the decoupling in AGC and AFC system. The decoupling system of AGC and AFC is decoupled by neural network which is trained by PSO. After the decoupling, the most important thing is to control the generalized system. So an advanced PID method is used, and to get the optimal parameter of the controller, a new adaptive PSO is presented to setting PID. The simulation conclusion indicated that the PID setting method and the training technique of neural network is simple and effective. And the control system is adaptive and anti-interference.

Keywords: adaptive PSO; AFC-AGC; decoupling; neural network

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1. Introduction

The flatness and gauge are the most important parameters of the strip rolling properties. The automatic flatness control (AFC) and automatic gauge control (AGC) combined system is nonlinear, time delay and multivariable decoupled real-time processing system. In order to get ideal controlling effect a novelty method based controller which combined the intelligent control method and the traditional control technique and it has been developing trend, especially when conventional control method can not get perfect control result. In this paper, in response to the great approximation ability of neural network, the BP neural network is adopted to decouple the combined control system of AFC and AGC.

PSO algorithm has so many characteristics such as simple structure, implementing easily and so on. But in fact the basic PSO also have disadvantage, for example it is easy to fall into local optimum and hard to get higher constriction precision in the searching procedure. Insufficient for the traditional algorithm a new adaptive PSO algorithm is proposed in this paper. And the algorithm is used to optimize decoupling neural network, thus avoiding the slow convergence velocity of traditional neural networks and easily falling into local minimum, "over-learning" and other shortcomings.

2. The Mathematical Model of AFC and AGC Control System

Assuming the last rack of a five-stand cold mill with a flatness control in work roll bending and gauge control hydraulic pressure regulation and can be approximated by first order inertia respectively, namely,

$$G_1(s) = \frac{K_1}{1+T_1 s}; \quad G_2(s) = \frac{K_2}{1+T_2 s}$$

Where, K_1, K_2 is gain coefficient, T_1, T_2 time constant.

To finishing simulation studying, firstly the mathematical model of the AFC and AGC control system by difference equation near the system work point is established.

The outlet thickness is chose as the control target variable and the gauge equation will be:

$$\Delta h = \Delta S + \frac{\Delta P}{C_P} + \frac{\Delta 2F}{C_F} \qquad (1)$$

Where, Δh is variation quantity of the outlet gauge; ΔS is variation quantity in roll gap; $\Delta 2F$ is force variation quantity of bending roll in the working roll system. C_P is Longitudinal stiffness coefficient for the roll mill; C_F is the bending stiffness coefficient.

Since flatness is a lateral stretching force difference that exist within strip, so the outlet lateral stretching force difference is chose to be the flatness control target variable, and the flatness equation is:

$$\Delta\sigma_1 = \frac{E}{h}[\frac{\Delta P}{K_P} - \frac{\Delta 2F}{K_F} - \frac{h\Delta H_w}{H} + \frac{h\Delta\sigma_0}{E}] \qquad (2)$$

Where, $\Delta\sigma_0$, $\Delta\sigma_1$ is the alterable variable of inlet and outlet lateral stretching force difference. H, h is the average gauge of inlet and outlet; K_P, K_F is lateral stiffness coefficient of rolling mill and bending roller. ΔH_ω is camber varying variable of inlet. E Rolled piece is elastic ratio.

Draught pressure difference equation is:

$$\Delta P = \frac{C_p Q}{C_p + Q}(\Delta H - \Delta S - \frac{\Delta 2F}{C_F}) \qquad (3)$$

Where, Q is rolled piece plastic coefficient.

Including equation (1) to (3) the combined mathematic model of AFC and AGC control system is

$$\begin{cases} \Delta\sigma_1 = \dfrac{E}{h}\left[\dfrac{1}{K_P} \cdot \dfrac{C_P Q}{C_P+Q}(\Delta H - \Delta S) - \left(\dfrac{C_P Q}{K_P \cdot (C_P+Q) \cdot C_F} - \dfrac{1}{K_F}\right)\Delta 2F - \dfrac{h\Delta H_\omega}{H} + \dfrac{h\Delta\sigma_0}{E}\right] \\ \Delta h = \dfrac{C_P}{C_P+Q}\Delta S + \dfrac{Q}{C_P+Q}\Delta H + \dfrac{C_P}{C_P+Q} \cdot \dfrac{1}{C_F}\Delta 2F \end{cases} \tag{4}$$

3. The Principle of a New Adaptive PSO Algorithm

The PSO algorithm is an evolutionary computation technique introduced by Kennedy and Eberhart in 1995. The underlying motivation for the development of PSO was social behavior of animals such as bird flocking. The PSO algorithm is similar to Genetic Algorithm (GA) in that the system is initialized with a population of random solutions. However, in PSO, each individual of the population, called particle, has an adaptable velocity, according to the search space which it moves over. Each particle keeps track of its coordinate in hyperspace, which are associated with the solution (flatness value) it has achieved so far. This value is called p_{best}. Another "best" value is called g_{best} that is obtained so far by any particle in the population and stored the overall best value.

In the basic version of the PSO algorithm each particle in the population manipulated according to the following assignment statements:

$$v_{id}^{t} = w v_{id}^{t-1} + c_1 r_1(\,)(p_{id} - x_{id}^{t-1}) + c_2 r_2(\,)(p_{gd} - x_{id}^{t-1}) \tag{5}$$

$$\boldsymbol{x}_{id}^{t} = \boldsymbol{x}_{id}^{t-1} + \boldsymbol{v}_{id}^{t} \cdot \boldsymbol{t} \tag{6}$$

Where v_{id}^{t} and x_{id}^{t} are the velocity and position of the i^{th} particle in the t^{th} iteration; p_{id} is the best position the i^{th} particle has accomplished at the $(t-1)^{th}$ iteration, and p_{gd} is the global best position achieved in the particle at the $(t-1)^{th}$ iteration. c_1 and c_2 are two positive constants called acceleration constants. r_1 and r_2 are two different random numbers in the range of 0 to 1.

Basic PSO algorithm has disadvantage such as easily falling into local optimum, hard to get greater convergence accuracy. To solve all the problems, an adaptive inertia weight and the maximum velocity is introduced into basic PSO algorithm to improve and restrict PSO algorithm, at the same time dynamic neighborhood and linearity congruence based adequate distribution initial strategy is used to establish an adaptive PSO.

The maximum velocity $v_{\max}$ determines the maximum change one particle can take during iteration, and determines the precision between current position and the global best position. If $v_{\max}$ is large value, the particle may fly beyond the best solution; If $v_{\max}$ is small value, particle cannot precede enough searches outside the partial good zone and sinks into the local optimized value. Usually we set the range of the particle as $v_{\max}$ and unified maximum velocity can also be set up, and can set the each dimension maximum velocity $v_{\max}$ according to dimension.

The inertia weight w keeps the movement inertial for the particle. It describes influence of the previous velocity to the current velocity, which means make the algorithm have the trend to extend the search space and have the ability to explore the new district, and there is the function to adjust the rate of velocity of particle. The inertia weight is decreased linearly from 0.9 to 0.4.

Linearity variety of the w:

$$w = w_{\max} - \left(w_{\max} - w_{\min} \big/ G_{\max} \right) G \tag{7}$$

Where: $w_{\max}$ is the maximum inertia weight, usually $w_{\max}$ =0.9; $w_{\min}$ is the minimum inertia weight, usually $w_{\min}$ =0.4; $G_{\max}$ is the maximum number of iteration; G is the current number of iteration.

In order to increase the searching precision when the generation increasing, a variational neighborhood operator is introduced. The specific procedure is: firstly computing the distance between the candidate individual and all the other individuals, there $dist(l)$ is the distance between the l one. The maximum distance is $\max inst$, and define a fraction namely $frac = 0.6 + 3.0 G_n / G_{\max}$ which is concerned with current generation G_n If $frac > 0.9$ and $frac > dist(l)/\max inst$, l_{best} is used in searching process, else g_{best} will be used.

In a word the basic step of adaptive algorithm is as follows:

1)setting parameters: choosing particle number m; setting the maximum iteration number $G_{\max}$; setting adaptive threshold ε; setting the accelerated constant c_1 and c_2; inertia weight w (including the maximum weight $w_{\max}$ and the minimum weight $w_{\min}$);

2) Initialing population, the initial velocity and the position of particles with a series of random number;

3) Computing the fitness value for each particle f_i;

4) If f_i current position is better than position of the individual optimum, then $p_{best} =$ the current position;

5) If f_i current position is better than position of the swarm optimum, then $g_{best} =$ the current position;

6) Updating the velocity: Computing the velocity of next generation according to the equation (5), and using maximum velocity to restrict the updating velocity,

if $\boldsymbol{v}_{id} < -v_{\max,d}$, then $\boldsymbol{v}_{id} = -v_{\max,d}$,

else if $\boldsymbol{v}_{id} > v_{\max,d}$, then $\boldsymbol{v}_{id} = v_{\max,d}$;

7) Updating the position: Computing the next generation position according equation (6), and in response to the position span restrict the new position;

8) Decreasing the inertia weight according to the equation (7);

9) Computing distance between the candidate individual and all other individuals, if $frac > 0.9$ and $frac > dist(l)/\max inst$, seaching l_{best}, else will be used g_{best};

10) If the adaptive threshold of fitness value is satisfied, then stop; otherwise continue;

11) If the maximum number of iteration doesn't reach the setting value, then go back to step.3, otherwise end.

4. AFC and AGC Decoupled Control System Based on PSO

4.1. The Structure of Control System

The diagram of AFC and AGC decoupled system is proposed in figure 1, in this diagram the control system compose of generalized control object, two conventional PID controllers and two neural network decouplers. In the system "control object" is integrality roll miller model include the depress device of rolling mills, hydraulic pressure of bending roller device and the transfer function of detection device. After decoupled by the neural network the generalized control object is becoming into two single variable control systems (namely AFC system and AGC system); Two traditional PID is used in AGC and AFC closed loop control systems. And in order to decouple the AGC and AFC combined control system all the parameter of decoupling neural network is adjusted by PSO model.

4.2. New Adaptive PSO Algorithm Optimizing Neural Network Decoupler

In order to decouple the generalized control object, firstly the controller should break with the object. Input signal get into the input channel x_1 of neural network decoupler. If the system is decoupled, y_2 will be 0. So the index function of decoupler NET_1 is:

$$f_1 = \frac{1}{2}\sum_{k=0}^{N}[y_2(k)]^2 \tag{8}$$

Similarly, the index function of neural network NET_2 is:

$$f_2 = \frac{1}{2}\sum_{k=0}^{N}[y_1(k)]^2 \tag{9}$$

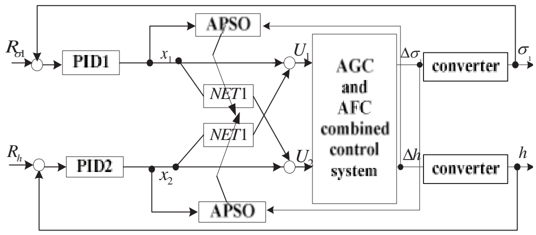


Fig. 1. AFC-AGC decoupling control system

Where N is training sample number.

The parameter of neural network is adjusting by adaptive PSO and The method is similar, so there the general training steps is proposed. In training process the input signal is phase step, namely when phase step signal carry in from x_1, there should be 0 in output y_2; when phase step signal carry in from x_2, there should be 0 in output y_1.

The decouple steps of the two input two output system by neural network:

1) Setting parameters: $m, G_{\max}, \varepsilon$ c_1 c_2 w ($w_{\max}$ and $w_{\min}$).

2) Initialing population, setting velocity vector, and then position vector which is a coded by weight of neural network;

3) Step phrase is inputted and then Computing the fitness value of each particle f_i by the equation (8) and (9);

4) If $f_i < f_{p_{best}}$, then p_{best} = current position; If $f_i < f_{g_{best}}$, then g_{best} = current position;

5) Updating the velocity: computing the velocity of next generation according to the equation (5), and using maximum velocity to restrict velocity,

if $\boldsymbol{v}_{id} < -v_{\max,d}$, then $\boldsymbol{v}_{id} = -v_{\max,d}$,

else if $\boldsymbol{v}_{id} > v_{\max,d}$, then $\boldsymbol{v}_{id} = v_{\max,d}$;

6) Updating the position: Computing the position of next generation according equation (6), and in response to the position span restrict the new position;

7) Decreasing the inertia weight according to the equation(7);

8) Computing distance between the candidate individual and all other individuals, if $frac > 0.9$ and $frac > dist(l)/\max inst$, searching l_{best}, else will be used g_{best};

9) If the threshold of fitness value is satisfied, then stop; otherwise continue;

10) If the maximum number of iteration doesn't reach the setting value, then go back to step.3), otherwise end;

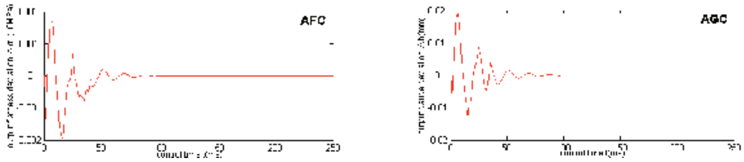
In the end of the training procedure, all the parameter should be recorded. There the couple system has been decoupled and coming into two SISO systems.

5. Experiment and Analyses

In the simulation experiment, neural network decoupler connects with AGC and AFC simulation system and is trained according to the training method front. All the parameters of neural network working in the simulation are got from training by PSO algorithm.

After decoupled it is imperative to find a good controller for the system. There still PSO algorithm is needed to get the optimal PID parameter. The parameter searching code scheme is to using K_p、 K_i、 K_d

as the position vector component, so the vector is $x = \{K_p, T_i, T_d\}$. The fitness function $J = \sum_{i=0}^{Q_1} T\left|e(i)\right|$, where Q_1 is defined according to the sampling period T（which is used to computing the space）and the adjusting time, and *e(i)* is the deviation which between the output value and the set value. According the above PID adjusting method, the parameter of PID controller is got and using in the simulation.



(a) Simulation result of AFC (b) Simulation result of AGC

Fig. 2. Simulation results with disturbance

The AGC and AFC combined control system is controlled by the PID controller whose parameter is adjusted by PSO algorithm in the experiment. First training the neural network in open loop system which is the series system of neural network decoupler and AGC and AFC combined control system, and then the weight and the threshold of the neural network is got. At last the PID controller will control the decoupled AGC and AFC control system, and the control result is showed in the figure 2. In this figure the output is flatness and gauges which is got in very short time when there is disturbance quantity.

6. Conclusion

In this experiment a new adaptive PSO algorithm is adopted to training neural network, and a decoupler is designed by using the neural network to decouple the AGC and AFC combined system, and the system is controlled by an advanced PID controller. Through the simulation it is obviously that this control system can get a satisfying control result when the AGC and AFC control system has disturbance quantity, and solving the AGC and AFC strong non-linearity and intensive couple problem effectively.

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